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EXAMINER

COLUCCI, MICHAEL C

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2626

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PAPER

Please find below and/or attached an Office communication concerning this application or proceeding.

The time period for reply, if any, is set in the attached communication.

Office Action Summary	Application No. 10/649,909	Applicant(s) DHARANIPRAGADA ET AL.	
	Examiner MICHAEL C. COLUCCI	Art Unit 2626	

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE 3 MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

- 1) ☒ Responsive to communication(s) filed on 24 March 2010.
- 2a) ☒ This action is **FINAL**. 2b) ☐ This action is non-final.
- 3) ☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

- 4) ☒ Claim(s) 1-15 and 17-27 is/are pending in the application.
- 4a) Of the above claim(s) _____ is/are withdrawn from consideration.
- 5) ☐ Claim(s) _____ is/are allowed.
- 6) ☒ Claim(s) 1-15 and 17-27 is/are rejected.
- 7) ☐ Claim(s) _____ is/are objected to.
- 8) ☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

- 9) ☐ The specification is objected to by the Examiner.
- 10) ☐ The drawing(s) filed on _____ is/are: a) ☐ accepted or b) ☐ objected to by the Examiner.
Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).
Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).
- 11) ☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

- 12) ☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).
- a) ☐ All b) ☐ Some * c) ☐ None of:
1. ☐ Certified copies of the priority documents have been received.
 2. ☐ Certified copies of the priority documents have been received in Application No. _____.
 3. ☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

- | | |
|--|---|
| 1) <input checked="" type="checkbox"/> Notice of References Cited (PTO-892) | 4) <input type="checkbox"/> Interview Summary (PTO-413) |
| 2) <input type="checkbox"/> Notice of Draftsperson's Patent Drawing Review (PTO-948) | Paper No(s)/Mail Date. _____ |
| 3) <input type="checkbox"/> Information Disclosure Statement(s) (PTO/SB/08) | 5) <input type="checkbox"/> Notice of Informal Patent Application |
| Paper No(s)/Mail Date _____ | 6) <input type="checkbox"/> Other: _____ |

DETAILED ACTION

Response to Arguments

1. Applicants arguments with respect to claims 1-15 and 17-27 have been considered but are moot in view of the new grounds of rejection. After further review of the claim amendments and prior art, Examiner has withdrawn Yang US 20010010039 A1 (hereinafter Yang) and has instead incorporated Naito et al. US 5983178 A (hereinafter Naito). Examiner believes that the combination of Neti in view of Naito and Kanevsky is more applicable to a difference in male/female phoneme models, wherein a threshold is applicable to choose between male or female models (Neti) via the improvement of gender-independent/dependent *phoneme* models and several trained models (Naito) wherein a gender independent phoneme model is created such as through the use of a Kullback Leibler distance to test if a topic change occurs (Kanevsky). For instance when a distance between two topics (e.g. male or female data) is lower than a threshold, a neutral topic is created (e.g. independent of male or female and the combination thereof). Please see new rejection below with Naito incorporated.

Claim Rejections - 35 USC § 103

2. The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

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(a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negated by the manner in which the invention was made.

3. Claims 1-16 are rejected under 35 U.S.C. 103(a) as being unpatentable over Neti et al. US 5953701 A (hereinafter Neti) in view of Naito et al. US 5983178 A (hereinafter Naito) and further in view of Kanevsky et al. US 6529902 (hereinafter Kanevsky).

Re claims 1, 6, and 11, Neti teaches a method for generating a speech recognition model, the method comprising:

receiving female speech training data (Abstract, Col. 3 lines 37-49, Col. 4 lines 10-29, male training data, female training data, gender specific phone state models);

generating female phoneme models based on the female speech training data (Abstract, Col. 3 lines 37-49, Col. 4 lines 10-29, male training data, female training data, gender specific phone state models);

receiving male speech training data (Abstract, Col. 3 lines 37-49, Col. 4 lines 10-29, male training data, female training data, gender specific phone state models);

generating male phoneme models based on the male speech training data (Abstract, Col. 3 lines 37-49, Col. 4 lines 10-29, male training data, female training data, gender specific phone state models);

determining a difference between each female phoneme model and each corresponding male phoneme model (Abstract, Col. 3 lines 37-49, Col. 4 lines 10-29, aligning data with gender independent data, male training data, female training data, gender specific phone state models)

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creating a gender-independent phoneme model

when the difference between the compared female phoneme model and the corresponding male phoneme model is less than predetermined value

However, Neti fails to teach creating a gender-independent/dependent phoneme models

Naito improves the model of Neti by incorporating gender independent phonemic models such as Naito teaches a clustering processor for training a predetermined initial hidden Markov model using a predetermined training algorithm based on the speech waveform data of speakers respectively belonging to the generated K clusters, which is stored in said first storage unit, thereby generating a plurality of K hidden Markov models corresponding to the plurality of K clusters

a second storage unit for storing the plurality of K hidden Markov models generated by said clustering processor;

a first speech recognition unit for recognizing speech of an inputted uttered speech signal of a recognition-target speaker with reference to a predetermined speaker independent phonemic hidden Markov model, and outputting a series of speech-recognized phonemes;

a speaker model selector for recognizing the speech of the inputted uttered speech signal, respectively, with reference to the plurality of K hidden Markov models stored in said second storage unit, based on the sequence of speech-recognized phonemes outputted from said first speech recognition unit, thereby calculating K

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likelihoods corresponding to the K hidden Markov models, and for selecting at least one hidden Markov model having the largest likelihood from the K hidden Markov models (Naito Col. 3 line 49—Col. 4 line 12).

Further, Naito teaches the recognition of phoneme dependent data which verifies whether data is independent of dependent, for example whether incoming data is within the range of a model or not (Naito Col. 15 line 54 - Col. 16 line 25).

Therefore, it would have been obvious to one of ordinary skill in the art at the time of the invention to modify the system of Naito to incorporate creating a gender-independent/dependent phoneme models as taught by Naito to allow for the selection of the best combination of phoneme models with the highest probability of having correctly recognized gender based speech in a phonemic model (Naito Col. 15 line 54 - Col. 16 line 25).

However, Naito in view of Kanevsky fails to teach creating a gender-independent phoneme model when the difference between the compared female phoneme model and the corresponding male phoneme model is less than predetermined value

adding, based on at least one criteria, one of the gender-independent phoneme model, or both the female phoneme model and the corresponding male phoneme model to the speech recognition model

Kanevsky teaches referring to FIG. 5, which illustrates on one-way direction process of separating features belonging to different topics and topic identification via a Kullback-Liebler distance method, texts that are labeled with different topics are

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denoted as 501 (e.g., topic 1), 502 (e.g., topic 2), 503 (e.g., topic 3), 504 (e.g., topic N) etc. Textual features can be represented as frequencies of words, a combination of two words, a combination of three words etc. On these features, one can define metrics that allow computation of a distance between different features. For example, if topics $T_{sub.i}$ give rise to probabilities $P(w_{sub.t} | T_{sub.t})$, where $w_{sub.t}$ run all words in some vocabulary, then a distance between two topics $T_{sub.i}$ and $T_{sub.j}$ can be computed as $\frac{1}{2} \sum_t |P(w_{sub.t} | T_{sub.i}) - P(w_{sub.t} | T_{sub.j})|$. Using Kullback-Liebler distances is consistent with likelihood ratio criteria that are considered above, for example, in Equation (6). Similar metrics could be introduced on tokens that include T-gram words or combination of tokens, as described above. Other features reflecting topics (e.g., key words) can also be used. For every subset of k features, one can define a k dimensional vector. Then, for two different k sets, one can define a Kullback-Liebler distance using frequencies of these k sets. Using Kullback-Liebler distance, one can check which pairs of topics are sufficiently separated from each other. Topics that are close in this metric could be combined together. For example, one can find that topics related to "LOAN" and "BANKS" are close in this metric, and therefore should be combined under a new label (e.g. "FINANCE"). Also, using these metrics, one can identify in each topic domain textual feature vectors ("balls") that are sufficiently separated from other "balls" in topic domains. These "balls" are shown in FIG. 5 as 505, 506, 504, etc. When such "balls" are identified, likelihood ratios as in FIG. 1, are computed for tokens from these "balls". (Kanevsky Col. 12 lines 15-56)

Further, Kanevsky teaches another instance of detecting whether a threshold is breached and topic similarity based on training data (Kanevsky Col. 13 lines 7-12 & lines 42-45).

Therefore, it would have been obvious to one of ordinary skill in the art at the time of the invention to modify the system of Neti in view of Naito to incorporate creating a gender-independent phoneme model when the difference between the compared female phoneme model and the corresponding male phoneme model is less than predetermined value and adding, based on at least one criteria, one of the gender-independent phoneme model, or both the female phoneme model and the corresponding male phoneme model to the speech recognition model as taught by Kanevsky to allow for the generation of combined data models with similar context such as male and female together (e.g. LOAN and BANKS) and also isolated data such as explicit male and female data (e.g. medical and legal), wherein topics are labeled as a group of phonemes or unigrams utilizing a Kullback-Liebler distance, where one can check which pairs of topics are sufficiently separated from each other provided a subset of k features, that one can define a k dimensional vector allowing computation of a distance between different features in the form of a trained group of model (Kanevsky Col. 12 lines 15-56).

Re claims 2, 7, and 12, Naito fails to teach the method at least one computer readable medium of claim 1, wherein the at least one criteria comprises a threshold

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value or an upper limit for the total number of phoneme models in the speech recognition model.

Naito improves the model of Neti by incorporating gender independent phonemic models such as Naito teaches a clustering processor for training a predetermined initial hidden Markov model using a predetermined training algorithm based on the speech waveform data of speakers respectively belonging to the generated K clusters, which is stored in said first storage unit, thereby generating a plurality of K hidden Markov models corresponding to the plurality of K clusters

a second storage unit for storing the plurality of K hidden Markov models generated by said clustering processor;

a first speech recognition unit for recognizing speech of an inputted uttered speech signal of a recognition-target speaker with reference to a predetermined speaker independent phonemic hidden Markov model, and outputting a series of speech-recognized phonemes;

a speaker model selector for recognizing the speech of the inputted uttered speech signal, respectively, with reference to the plurality of K hidden Markov models stored in said second storage unit, based on the sequence of speech-recognized phonemes outputted from said first speech recognition unit, thereby calculating K likelihoods corresponding to the K hidden Markov models, and for selecting at least one hidden Markov model having the largest likelihood from the K hidden Markov models (Naito Col. 3 line 49—Col. 4 line 12).

Further, Naito teaches the recognition of phoneme dependent data which verifies whether data is independent of dependent, for example whether incoming data is within the range of a model or not (Naito Col. 15 line 54 - Col. 16 line 25).

Therefore, it would have been obvious to one of ordinary skill in the art at the time of the invention to modify the system of Neti to incorporate a plurality of phoneme models as taught by Naito to allow for the selection of the best combination of phoneme models with the highest probability of having correctly recognized gender based speech in a phonemic model (Naito Col. 15 line 54 - Col. 16 line 25).

However, Neti in view of Naito fails to teach a threshold value or an upper limit for the total number of phoneme models in the speech recognition model

Kanevsky teaches referring to FIG. 5, which illustrates on one-way direction process of separating features belonging to different topics and topic identification via a Kullback-Liebler distance method, texts that are labeled with different topics are denoted as 501 (e.g., topic 1), 502 (e.g., topic 2), 503 (e.g., topic 3), 504 (e.g., topic N) etc. Textual features can be represented as frequencies of words, a combination of two words, a combination of three words etc. On these features, one can define metrics that allow computation of a distance between different features. For example, if topics $T_{sub.i}$ give rise to probabilities $P(w_{sub.t} | T_{sub.t})$, where $w_{sub.t}$ run all words in some vocabulary, then a distance between two topics $T_{sub.i}$ and $T_{sub.j}$ can be computed as $\sum_{t=1}^n |P(w_{sub.t} | T_{sub.i}) - P(w_{sub.t} | T_{sub.j})|$. Using Kullback-Liebler distances is consistent with likelihood ratio criteria that are considered above, for example, in Equation (6). Similar metrics

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could be introduced on tokens that include T-gram words or combination of tokens, as described above. Other features reflecting topics (e.g., key words) can also be used. For every subset of k features, one can define a k dimensional vector. Then, for two different k sets, one can define a Kullback-Liebler distance using frequencies of these k sets. Using Kullback-Liebler distance, one can check which pairs of topics are sufficiently separated from each other. Topics that are close in this metric could be combined together. For example, one can find that topics related to "LOAN" and "BANKS" are close in this metric, and therefore should be combined under a new label (e.g. "FINANCE"). Also, using these metrics, one can identify in each topic domain textual feature vectors ("balls") that are sufficiently separated from other "balls" in topic domains. These "balls" are shown in FIG. 5 as 505, 506, 504, etc. When such "balls" are identified, likelihood ratios as in FIG. 1, are computed for tokens from these "balls". (Kanevsky Col. 12 lines 15-56)

Further, Kanevsky teaches another instance of detecting whether a threshold is breached and topic similarity based on training data (Kanevsky Col. 13 lines 7-12 & lines 42-45).

Therefore, it would have been obvious to one of ordinary skill in the art at the time of the invention to modify the system of Neti in view of Naito to incorporate a threshold value or an upper limit for the total number of phoneme models in the speech recognition model as taught by Kanevsky to allow for the generation of combined data models with similar context such as male and female together (e.g. LOAN and BANKS) and also isolated data such as explicit male and female data (e.g. medical and legal),

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wherein topics are labeled as a group of phonemes or unigrams utilizing a Kullback-Liebler distance, where one can check which pairs of topics are sufficiently separated from each other provided a subset of k features, that one can define a k dimensional vector allowing computation of a distance between different features in the form of a trained group of model (Kanevsky Col. 12 lines 15-56 Fig. 5 topic clusters).

Re claims 3, 8, and 13, Neti fails to teach the method of claim 1, wherein determining the difference includes calculating a Kullback Leibler distance between the each female phoneme model and the each corresponding male phoneme model.

However, Neti fails to teach creating a gender-independent/dependent phoneme models

Naito improves the model of Neti by incorporating gender impendent phonemic models such as Naito teaches a clustering processor for training a predetermined initial hidden Markov model using a predetermined training algorithm based on the speech waveform data of speakers respectively belonging to the generated K clusters, which is stored in said first storage unit, thereby generating a plurality of K hidden Markov models corresponding to the plurality of K clusters

a second storage unit for storing the plurality of K hidden Markov models generated by said clustering processor;

a first speech recognition unit for recognizing speech of an inputted uttered speech signal of a recognition-target speaker with reference to a predetermined

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speaker independent phonemic hidden Markov model, and outputting a series of speech-recognized phonemes;

a speaker model selector for recognizing the speech of the inputted uttered speech signal, respectively, with reference to the plurality of K hidden Markov models stored in said second storage unit, based on the sequence of speech-recognized phonemes outputted from said first speech recognition unit, thereby calculating K likelihoods corresponding to the K hidden Markov models, and for selecting at least one hidden Markov model having the largest likelihood from the K hidden Markov models (Naito Col. 3 line 49—Col. 4 line 12).

Further, Naito teaches the recognition of phoneme dependent data which verifies whether data is independent of dependent, for example whether incoming data is within the range of a model or not (Naito Col. 15 line 54 - Col. 16 line 25).

Therefore, it would have been obvious to one of ordinary skill in the art at the time of the invention to modify the system of Neti to incorporate creating a gender-independent/dependent phoneme models as taught by Naito to allow for the selection of the best combination of phoneme models with the highest probability of having correctly recognized gender based speech in a phonemic model (Naito Col. 15 line 54 - Col. 16 line 25).

However, Neti in view of Naito fails to teach determining the difference includes calculating a Kullback Leibler distance

Kanevsky teaches referring to FIG. 5, which illustrates on one-way direction process of separating features belonging to different topics and topic identification via a Kullback-Liebler distance method, texts that are labeled with different topics are denoted as 501 (e.g., topic 1), 502 (e.g., topic 2), 503 (e.g., topic 3), 504 (e.g., topic N) etc. Textual features can be represented as frequencies of words, a combination of two words, a combination of three words etc. On these features, one can define metrics that allow computation of a distance between different features. For example, if topics $T_{sub.i}$ give rise to probabilities $P(w_{sub.t} | T_{sub.t})$, where $w_{sub.t}$ run all words in some vocabulary, then a distance between two topics $T_{sub.i}$ and $T_{sub.j}$ can be computed as $\sum_{t=1}^n |P(w_{sub.t} | T_{sub.i}) - P(w_{sub.t} | T_{sub.j})|$. Using Kullback-Liebler distances is consistent with likelihood ratio criteria that are considered above, for example, in Equation (6). Similar metrics could be introduced on tokens that include T-gram words or combination of tokens, as described above. Other features reflecting topics (e.g., key words) can also be used. For every subset of k features, one can define a k dimensional vector. Then, for two different k sets, one can define a Kullback-Liebler distance using frequencies of these k sets. Using Kullback-Liebler distance, one can check which pairs of topics are sufficiently separated from each other. Topics that are close in this metric could be combined together. For example, one can find that topics related to "LOAN" and "BANKS" are close in this metric, and therefore should be combined under a new label (e.g. "FINANCE"). Also, using these metrics, one can identify in each topic domain textual feature vectors ("balls") that are sufficiently separated from other "balls" in topic domains. These "balls" are shown in FIG. 5 as 505, 506, 504, etc. When such "balls"

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are identified, likelihood ratios as in FIG. 1, are computed for tokens from these "balls".

(Kanevsky Col. 12 lines 15-56)

Further, Kanevsky teaches another instance of detecting whether a threshold is breached and topic similarity based on training data (Kanevsky Col. 13 lines 7-12 & lines 42-45).

Therefore, it would have been obvious to one of ordinary skill in the art at the time of the invention to modify the system of Neti in view of Naito to incorporate determining the difference includes calculating a Kullback Leibler distance as taught by Kanevsky to allow for the generation of combined data models with similar context such as male and female together (e.g. LOAN and BANKS) and also isolated data such as explicit male and female data (e.g. medical and legal), wherein topics are labeled as a group of phonemes or unigrams utilizing a Kullback-Liebler distance, where one can check which pairs of topics are sufficiently separated from each other provided a subset of k features, that one can define a k dimensional vector allowing computation of a distance between different features in the form of a trained group of model (Kanevsky Col. 12 lines 15-56).

Re claims 4, 9, and 14, Neti in view of Naito fails to teach the method of claim 3, wherein the difference is a threshold Kullback Leibler distance quantity.

Kanevsky teaches the Kullback-Leibler distance (Kanevsky Col. 5, lines 9-11) between any two topics is at least h, where h ~s some sufficiently large threshold, also

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Kanevsky teaches (Kanevsky Col. 12, lines 44-47) that while using the Kullback-Leibler distance, one can check which pairs of topics are sufficiently separated from each other, and that topics that are close in this metric could be combined together).

Kanevsky also explicitly teaches how a difference is sufficient, such as classifying data groups when compared, and also creating independence from classification if there is no topic discovered (Kanevsky Col. 5 lines 8-25).

Therefore, it would have been obvious to one of ordinary skill in the art at the time of the invention to modify the system of Neti in view of Naito to incorporate whether the model information is insignificant is based on a threshold Kullback Leibler distance quantity as taught by Kanevsky to allow for an improved language modeling for automatic speech decoding and differentiation between data groups, wherein a sufficiently large threshold indicates either separate or combinational probabilities (Kanevsky Col. 2, lines 50-52).

Re claims 5, 10, and 15, Neti teaches method of claim 1, wherein the female phoneme models, male phoneme models, and gender-independent phoneme models are Gaussian mixture models (Neti Col. 3 lines 50-67).

However, Neti fails to teach creating a gender-independent/dependent phoneme models

Naito improves the model of Neti by incorporating gender independent phonemic models such as Naito teaches a clustering processor for training a predetermined initial hidden Markov model using a predetermined training algorithm based on the speech

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waveform data of speakers respectively belonging to the generated K clusters, which is stored in said first storage unit, thereby generating a plurality of K hidden Markov models corresponding to the plurality of K clusters

a second storage unit for storing the plurality of K hidden Markov models generated by said clustering processor;

a first speech recognition unit for recognizing speech of an inputted uttered speech signal of a recognition-target speaker with reference to a predetermined speaker independent phonemic hidden Markov model, and outputting a series of speech-recognized phonemes;

a speaker model selector for recognizing the speech of the inputted uttered speech signal, respectively, with reference to the plurality of K hidden Markov models stored in said second storage unit, based on the sequence of speech-recognized phonemes outputted from said first speech recognition unit, thereby calculating K likelihoods corresponding to the K hidden Markov models, and for selecting at least one hidden Markov model having the largest likelihood from the K hidden Markov models (Naito Col. 3 line 49—Col. 4 line 12).

Further, Naito teaches the recognition of phoneme dependent data which verifies whether data is independent of dependent, for example whether incoming data is within the range of a model or not (Naito Col. 15 line 54 - Col. 16 line 25).

Therefore, it would have been obvious to one of ordinary skill in the art at the time of the invention to modify the system of Naito to incorporate creating a gender-independent/dependent phoneme models as taught by Naito to allow for the selection of

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the best combination of phoneme models with the highest probability of having correctly recognized gender based speech in a phonemic model (Naito Col. 15 line 54 - Col. 16 line 25).

4. Claims 17-27 are rejected under 35 U.S.C. 103(a) as being unpatentable over Neti et al. US 5953701 A (hereinafter Neti) in view of Wark US 20030231775 (hereinafter Wark) and further in view of Naito et al. US 5983178 A (hereinafter Naito).

Re claims 17, 21, and 24, Neti teaches a system for recognizing speech data from an audio stream originating from one of a plurality of data classes ([0094]), each data class having a class-dependent phoneme model, the system comprising:

a computer processor (Col. 6 lines 24-49);

a receiving module configured to receive a current feature vector of the audio stream (Col. 6 lines 24-49);

a first computing module configured to compute a current best estimates (Col. 3 lines 50-67) that the current feature vector belongs to one of the plurality of data classes (Col. 5 lines 9-21);

However, Neti fails to teach a second computing module configured to compute an accumulated confidence values for each of the plurality of data class that the current feature vector belongs to each one of the plurality of data classes, the confidence value

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for each data class of the plurality of data classes based on the current best estimate for the data class and on previous confidence values for the data class, the previous confidence values associated with previous feature vectors of the audio stream;

a weighing module configured to weigh the class-dependent phoneme models based on the accumulated confidence values; and

a recognizing module configured to recognize the current feature vector (based on the weighted class-dependent phoneme models; and

Wark teaches classification of homogeneous segments, a number of statistical features are extracted from each segment. Whilst previous systems extract from each segment a feature vector, and then classify the segments based on the distribution of the feature vectors, method 200 divides each homogenous segment into a number of smaller sub-segments, or clips hereinafter, with each clip large enough to extract a meaningful feature vector f from the clip. The clip feature vectors f are then used to classify the segment from which it is extracted based on the characteristics of the distribution of the clip feature vectors f . The key advantage of extracting a number of feature vectors f from a series of smaller clips rather than a single feature vector for a whole segment is that the characteristics of the distribution of the feature vectors f over the segment of interest may be examined. Thus, whilst the signal characteristics over the length of the segment are expected to be reasonably consistent, by virtue of the segmentation algorithm, some important characteristics in the distribution of the feature vectors f over the segment of interest is significant for classification purposes (Wark [0094])

Further, Wark teaches the ability to decide whether the segment should be assigned the label of the class with the highest score, or labeled as "unknown", a confidence score is calculated. This is achieved by taking the difference of the top two model scores $s_{p,q}$ and $s_{q,p}$, and normalizing that difference by the distance measure D_{pq} between their class models p and q . This is based on the premise that an easily identifiable segment should be a lot closer to the model it belongs to than the next closest model. With further apart models, the model scores $s_{p,q}$ should also be well separated before the segment is assigned the class label of the class with the highest score (Wark [0146] & Fig. 4, adjacent, previous and current segment/frame).

Therefore, it would have been obvious to one of ordinary skill in the art at the time of the invention to modify the system of Neti to incorporate a second computing module configured to compute an accumulated confidence values for each of the plurality of data class that the current feature vector belongs to each one of the plurality of data classes, the confidence value for each data class of the plurality of data classes based on the current best estimate for the data class and on previous confidence values for the data class, the previous confidence values associated with previous feature vectors of the audio stream, a weighing module configured to weigh the class-dependent phoneme models based on the accumulated confidence values, and a recognizing module configured to recognize the current feature vector (based on the weighted class-dependent phoneme models as taught by Wark to allow for normalization of a difference by a distance, whereby an easily identifiable segment should be a lot closer to the model it belongs to than the next closest model (Wark

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[0146]), wherein a confidence score or score is used to better classify speech, whereby segments of feature vectors are classified, making important characteristics in adjacent, current, and previous frames in the distribution of the feature vectors more apparent (Wark [0094]), wherein the best model score is achieved (Wark [0129-0130]).

However, Netiin view of Wark fails to teach creating a class-independent/dependent phoneme models

Naito improves the model of Neti by incorporating gender impendent phonemic models such as Naito teaches a clustering processor for training a predetermined initial hidden Markov model using a predetermined training algorithm based on the speech waveform data of speakers respectively belonging to the generated K clusters, which is stored in said first storage unit, thereby generating a plurality of K hidden Markov models corresponding to the plurality of K clusters

a second storage unit for storing the plurality of K hidden Markov models generated by said clustering processor;

a first speech recognition unit for recognizing speech of an inputted uttered speech signal of a recognition-target speaker with reference to a predetermined speaker independent phonemic hidden Markov model, and outputting a series of speech-recognized phonemes;

a speaker model selector for recognizing the speech of the inputted uttered speech signal, respectively, with reference to the plurality of K hidden Markov models

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stored in said second storage unit, based on the sequence of speech-recognized phonemes outputted from said first speech recognition unit, thereby calculating K likelihoods corresponding to the K hidden Markov models, and for selecting at least one hidden Markov model having the largest likelihood from the K hidden Markov models (Naito Col. 3 line 49—Col. 4 line 12).

Further, Naito teaches the recognition of phoneme dependent data which verifies whether data is independent of dependent, for example whether incoming data is within the range of a model or not (Naito Col. 15 line 54 - Col. 16 line 25).

Therefore, it would have been obvious to one of ordinary skill in the art at the time of the invention to modify the system of Neti to incorporate class-dependent phoneme models as taught by Naito to allow for the selection of the best combination of phoneme models with the highest probability of having correctly recognized gender based speech in a phonemic model (Naito Col. 15 line 54 - Col. 16 line 25).

Re claims 18, 22, and 25, Neti teaches the method of claim 17, wherein computing the current vector probability includes estimating a posteriori class probability for the current feature vector (Col. 2 lines 1-8))

Re claims 19, 23, and 26, Neti fails to teach the method of claim 17, wherein computing the accumulated confidence level further comprising weighing the current vector probability more than the previous vector probabilities.

Wark teaches classification of homogeneous segments, a number of statistical features are extracted from each segment. Whilst previous systems extract from each segment a feature vector, and then classify the segments based on the distribution of the feature vectors, method 200 divides each homogenous segment into a number of smaller sub-segments, or clips hereinafter, with each clip large enough to extract a meaningful feature vector f from the clip. The clip feature vectors f are then used to classify the segment from which it is extracted based on the characteristics of the distribution of the clip feature vectors f . The key advantage of extracting a number of feature vectors f from a series of smaller clips rather than a single feature vector for a whole segment is that the characteristics of the distribution of the feature vectors f over the segment of interest may be examined. Thus, whilst the signal characteristics over the length of the segment are expected to be reasonably consistent, by virtue of the segmentation algorithm, some important characteristics in the distribution of the feature vectors f over the segment of interest is significant for classification purposes (Wark [0094])

Further, Wark teaches the ability to decide whether the segment should be assigned the label of the class with the highest score, or labeled as "unknown", a confidence score is calculated. This is achieved by taking the difference of the top two model scores $.sub.p$ and $.sub.q$, and normalizing that difference by the distance measure $D.sub.pq$ between their class models p and q . This is based on the premise that an easily identifiable segment should be a lot closer to the model it belongs to than the next closest model. With further apart models, the model scores $.sub.c$ should also

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be well separated before the segment is assigned the class label of the class with the highest score (Wark [0146] & Fig. 4, adjacent, previous and current segment/frame).

Therefore, it would have been obvious to one of ordinary skill in the art at the time of the invention to modify the system of Neti to incorporate computing the accumulated confidence level further comprising weighing the current vector probability more than the previous vector probabilities as taught by Wark to allow for normalization of a difference by a distance, whereby an easily identifiable segment should be a lot closer to the model it belongs to than the next closest model (Wark [0146]), wherein a confidence score or score is used to better classify speech, whereby segments of feature vectors are classified, making important characteristics in adjacent, current, and previous frames in the distribution of the feature vectors more apparent (Wark [0094]).

Re claims 20 and 27, Neti teaches the method of claim 17, further comprising determining if another feature vector is available for analysis (Col. 6 lines 24-49).

Conclusion

5. The prior art made of record and not relied upon is considered pertinent to applicant's disclosure. US 6556969 B1, US 20030110038 A1.

6. Applicant's amendment necessitated the new ground(s) of rejection presented in this Office action. Accordingly, **THIS ACTION IS MADE FINAL**. See MPEP

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§ 706.07(a). Applicant is reminded of the extension of time policy as set forth in 37 CFR 1.136(a).

A shortened statutory period for reply to this final action is set to expire THREE MONTHS from the mailing date of this action. In the event a first reply is filed within TWO MONTHS of the mailing date of this final action and the advisory action is not mailed until after the end of the THREE-MONTH shortened statutory period, then the shortened statutory period will expire on the date the advisory action is mailed, and any extension fee pursuant to 37 CFR 1.136(a) will be calculated from the mailing date of the advisory action. In no event, however, will the statutory period for reply expire later than SIX MONTHS from the date of this final action.

Any inquiry concerning this communication or earlier communications from the examiner should be directed to Michael C. Colucci whose telephone number is (571)-270-1847. The examiner can normally be reached on 9:30 am - 6:00 pm, Monday-Friday.

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Richemond Dorvil can be reached on (571)-272-7602. The fax phone number for the organization where this application or proceeding is assigned is 571-273-8300.

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